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Evaluation of Angular Velocity Data from Inertial Measurement Units for Use in Clinical Settings

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EVALUATION OF ANGULAR VELOCITY DATA FROM INERTIAL
MEASUREMENT UNITS FOR USE IN CLINICAL SETTINGS

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
Of the Requirements for the Degree
Master of Science
Bioengineering

by
Chelsea L. Ex-Lubeskie
May 2013

Accepted by:
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ABSTRACT

Evaluating the human gait cycle with inertial measurement units (IMU) may prove beneficial for applications such as diagnoses of musculoskeletal diseases and assessment of rehabilitation regimes. An IMU system is potentially applicable for diagnosing and assessing rehabilitation outcomes for a variety of neuromuscular diseases since it is small, portable, and less expensive than a camera system. IMUs directly measure angular velocity, whereas position data from a camera system must be processed twice to obtain this information. The purpose of this research is to determine repeatability of IMU angular velocity data, and agreement between angular velocity data from an IMU system and a camera system during normal gait. From this data, the feasibility of using IMU systems in clinical or rehabilitative settings for obtaining reliable angular velocity data will be determined.

Lower limb motion data was collected simultaneously from six XSens MTx IMUs (XSens Technologies, Enschede, The Netherlands) and an 8-camera Qualisys Motion Capture system (Pro-Reflex, 240 Hz system). Each IMU consists of three orthogonal accelerometers, gyroscopes, and magnetometers. Data from 4 subjects (3 males, 2 females) were collected after an initialization technique before each trial to reduce effects of electro-magnetic interference with the IMUs. Knee joint angular velocities (G_x , G_y , G_z) corresponding to appropriate knee joint angles (flexion/extension, adduction/abduction, and internal/external rotations) from both systems were used in this analysis. Coefficients of variation (COV) were calculated for both IMU and camera data to determine variability of data from both systems. Knee joint Average angular velocities

from both systems for each subject and limb were plotted together to visually evaluate correlation between data sets. F-test analyses were performed on linear models of the data to determine areas of co-linearity within the gait cycle, and at different intervals of angular velocities.

The IMUs had lower COV's than the camera system, likely due to the fact that the IMUs directly measure angular velocity, and camera system derives angular velocity from position data. However, these differences were not statistically different, likely due to variability within trials for individual subjects. Linearity between camera system and IMU angular velocity was visually observed only about the flexion/extension axis during segments of the gait cycle occurring from 0-4% (heel strike) and 65-100% (swing phase) of the gait cycle. Comparisons about the adduction/abduction and internal/external axes showed evidence of linearity for lower angular velocities. Linear regression statistics showed that the only correlational trend between the two systems was around 8-12% of the gait cycle for all three rotational axes. This may be due to drift of the IMU data. Although the camera system is the “gold standard” in motion analysis, IMUs may be used for applications in which angular velocity for a flexion-extension movement at low joint angles is being evaluated. Future studies will include a larger sample population, and evaluate specific movements within human gait that affect drift of the IMUs. In addition, other IMU system designs could be evaluated for clinical use, and other algorithms that further reduce the effects of drift should be implemented.

DEDICATION

I would like to dedicate this manuscript to all of my family and friends that have supported, encouraged, and pushed me to keep going over my years at Clemson University. Thank you to Ashley, Laura, Shelley, Lauren C, Lauren E, Courtney, Andrew, and Shawqi for being true and constant friends to me over the years, and to Megan, Amelie, Caleb, and Justin for the encouragement and laughs this past year. To my brother, Connor, thank you for being a wonderful sibling and helping me to remember to have fun. I would most importantly like to thank my parents for all of their love. They have shown unwavering support in my personal and academic endeavors, and would not be where I am today without their faith in me.

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CHAPTER 1 - INTRODUCTION

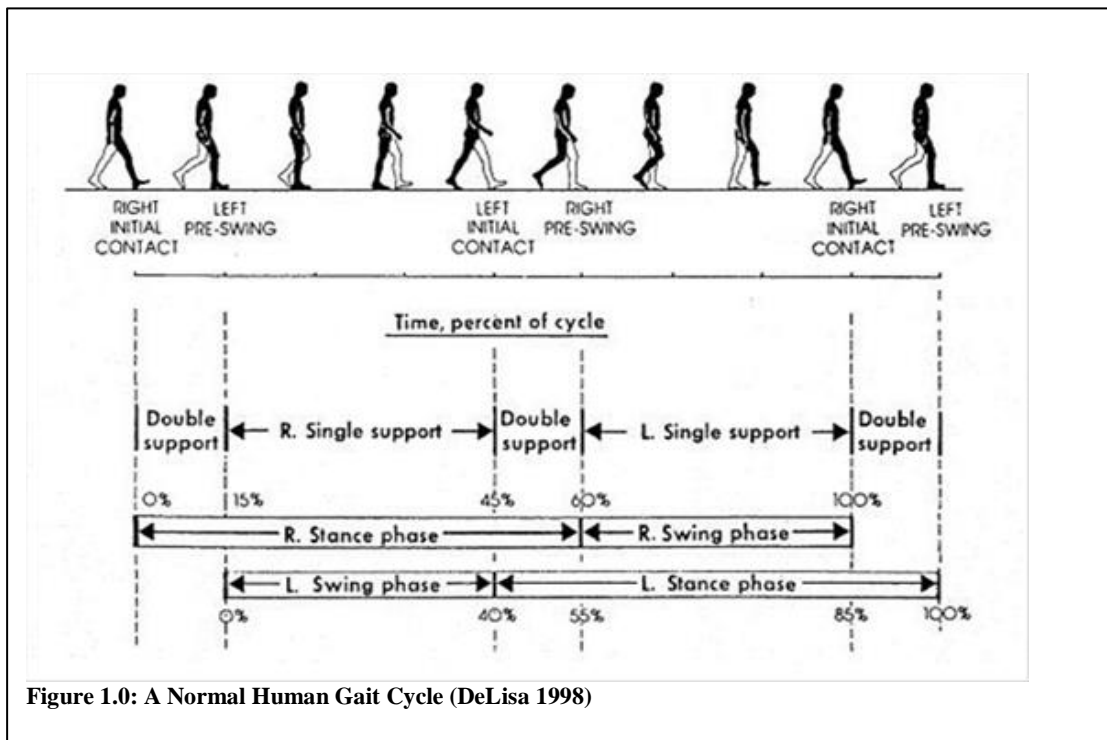
Background

The ability to quantitatively measure gait kinematics for a variety of purposes spanning from rehabilitation to evaluating osteoarthritis progression is crucial for patient outcomes. Motion capture systems have the ability to define spatio-temporal, kinematic, and kinetic parameters which is advantageous for quantifying patient outcomes throughout recovery, or over the lifetime of a disease that affects their gait.

Human Gait

Human gait, or locomotion, is how people walk, and can be normal or abnormal. The physical activity of walking involves not only the musculoskeletal system, but also the central nervous system and peripheral nervous system (Sadeghi et al. 2000, Vaughan, Davis & O'Connor 1992). For a walking event to occur, there are a sequence of events that occur starting at the central nervous system. First, the central nervous system center that controls locomotion must be registered and activated to send a signal; then a gait signal is sent to the peripheral nervous system. The muscles contract and forces and moments are generated across the synovial joints. Skeletal segments regulate the joint moments and forces, the segments move, and finally ground reaction forces are generated from moving (Vaughan, Davis & O'Connor 1992).

A gait cycle is broken into two main phases, swing and stance. Stance phase accounts for approximately 60% of the gait cycle while swing phase accounts for 40% (Vaughan, Davis & O'Connor 1992, DeLisa 1998).



A complete gait cycle is defined as the sequence of motion that occurs from heel strike to heel strike of the same foot. Figure 1.0 (DeLisa 1998) shows a breakdown of the specific phases of the gait cycle and the stance and swing phases can be further broken down. The stance phase can be divided into single and double limb support, while the swing phase consists of initial swing, midswing, and terminal swing. The muscles of the leg including the quadriceps, gastrocnemius, soleus, gluteus, and others aid in helping act as shock absorbers, stabilizers, accelerators, and for general control of the feet and legs (Vaughan, Davis & O'connor 1992, DeLisa 1998). It is important to note that when there is pathology affecting locomotion, the time spent in each of swing and stance phase may change. For example, a patient who has osteoarthritis in their left hip will spent almost

80% of their time in the stance phase for their unaffected limb, allowing for them to rely on that limb and likely reduce their pain (Vaughan, Davis & O'connor 1992).

The body acts in a sinusoidal motion with respect to the center of mass (COM), this is located midway between hip joints, and anterior to the second sacral vertebra. The body's COM has both vertical and lateral displacement, which both average about 5 cm. The body moves in a relatively low energy state with normal gait patterns, however, pathology can affect the vertical and lateral displacements of the COM, and in turn increase the energy expenditure of locomotion. The observation of COM displacement is referred to as the smoothness of gait, and is a visual clinical observation used in diagnosing or evaluating patients (DeLisa 1998).

Gait Analysis

Gait analysis is a commonly used tool in many clinical and rehabilitation settings. Research surrounding gait analysis has been going on since the 19th century, and its widespread use concerning biomechanics and bioengineering began with the commercialization of video camera systems (Tao et al. 2012). This type of analysis can provide valuable kinetic, kinematic, and EMG data that is useful in treating a variety of disorders or evaluating rehabilitation progress. Kinematics of joints describes the movements of joints and their various components. Kinetic data focuses on the forces and moments around the joints, and often kinematic data is used in conjunction with kinetic data. EMG data provides information about muscle activity and activation (Tao et al. 2012, Aminian et al. 2004). Kinematic data (joint angles, velocities, and accelerations) is able to provide a great deal of insight into gait abnormalities (Jasiewicz et al. 2006).

Camera Based Gait Analysis Systems

Considered the gold standard for human motion analysis, optoelectric stereophotogrammetric measurements from optical (camera) gait analysis systems are currently used in gait laboratories. Their reliability, protocols, and joint convention are known and have been widely adopted in clinical settings (Benedetti et al. 1998). These optical motion analysis systems use sets of cameras, passive or active markers, and software to calculate joint kinematics and spatio-temporal parameters. When paired with a force plate, gait kinetics can be obtained from this type of system (Tong, Granat 1999). Six cameras are needed for a typical gait analysis data collection in order to obtain 3D kinematics. The markers on the subject are registered through the cameras as points in space, and through mathematical procedures are integrated to obtain angles, displacement, velocity, and acceleration (Churchill, Halligan & Wade 2002). These systems have been readily used in multiple applications including biomechanics, gait analysis, rehab, and sports science (Qualisys Motion Capture). Two popular systems that are used for gait and rehabilitation include the Qualisys Motion Capture System and the Vicon Motion Capture System.

While these optical motion analysis systems are well-established and reliable, they are not without limitations. Camera-based systems require a dedicated lab space (only used for this application), expensive equipment, lengthy patient setup times, and lengthy data processing times. Subjects are restricted to a walking confined area in the laboratory, and therefore the system can only capture a small amount of continuous data (Tao et al. 2012, Tong, Granat 1999). In addition to these issues, a gait laboratory

requires specially trained personnel to apply the markers (Aminian et al. 2004). The markers can also be obscured from sight while a study is being conducted, resulting in incomplete data (Mayagoitia, Nene & Veltink 2002). Soft tissue artifacts pose an issue for this technology. Due to this issue, camera based gait systems have a limitation in measuring internal/external and varus/valgus rotations as precisely as flexion/extension rotations of the knee. Measurements can be improved by using intracortical pins that connect directly to the bone, but this invasive procedure is obviously not conducive to the patient (Sadeghi et al. 2000). In addition, optional motion analysis systems do not directly measure joint angles or joint angular velocities. 3D optical tracking systems use various calibration techniques, whether it be with a wand with reflective markers attached or the patients standing with the markers in place, to orient the markers in a reference frame and identify specific anatomical landmarks including feet, knees, and hips (Churchill, Halligan & Wade 2002, Windolf, Götzen & Morlock 2008). A mathematical procedure takes the views of the markers from several cameras and integrates them into 3D position data within space. From this data, joint angles can be calculated from subtracting position data, and joint angular velocities can be obtained by differentiating joint angles. There is no standardized calibration or reference frame; however most optical motion systems use the right hand rule for 3D joint analysis (Churchill, Halligan & Wade 2002, Soutas-Little 1998). Considering the calibration technique and numerous mathematical steps taken to obtain angular velocity, error could be acquired during this process.

Costs of setting up and running a gait laboratory with an optical motion analysis are high; additionally, costs to the patient are high both in terms of money and time. The

total time for a patient for gait analysis is around 2 hours, and costs about \$2000, of which approximately \$500 is reimbursed (Simon 2004). On average, a gait laboratory requires 70 therapist hours, 120 technician hours, and 25 clerical hours per month. Hospitals do not typically have the budget to allow for gait laboratories, and if they do, the laboratory typically focuses on only one gait disorder, such as cerebral palsy, leaving victims of stroke or Parkinson's with less effective clinical measurements and observation techniques (Churchill, Halligan & Wade 2002).

In 1999, the NIH stated that future research studies concerning gait analysis needed to be focused on efficacy, outcomes, and cost-effectiveness of these procedures (Simon 2004). There is a push to take gait analysis out of the laboratory, and into environments that allow more varied motions. Motor performance as measured in the laboratory setting may not accurately reflect actual functionality seen in normal life (Favre et al. 2008). An example is stair climbing, which has been proven to be a more critical pre-clinical assessment than walking for fall risk in geriatric patients. Stair climbing cannot be performed inside a confined laboratory space. It would be advantageous to have a more cost-effective, less bulky, and more adaptable technology that can be worn for long periods of time for data collection (Bamberg et al. 2008, Bergmann, Mayagoitia & Smith 2009). There are all unmet needs that the “gold standard” optical motion analysis systems will not be able to satisfy.

MEMS Based Motion Tracking: Inertial Measurement Units

In order to mitigate many of the problems seen with optical motion analysis systems, alternative solutions have arisen for use in 3D motion analysis within the last 20

years (Tao et al. 2012). Advances in MEMS (microelectromechanical systems) have allowed for light, low cost, and low power body mounted sensors to be used in human gait analysis and biomechanics research. These systems allow data collection outside of conventional gait laboratory spaces, which satisfies the need for an ambulatory motion analysis system (Favre et al. 2009). MEMS sensors may include accelerometers, gyroscopes, and/or magnetometers (Gouwanda, Senanayake 2008). Accelerometers are able to capture linear velocity and acceleration, gyroscopes capture angular velocity and acceleration, and magnetometers allow for a relative reference frame obtained by magnetic north to indicate the ground reference for all of the axes to use (Caruso 2000). However, the use of magnetometers inside is limited due to their interaction with ferrous metals that are typically present in indoor laboratories, which can affect the data (Roetenberg 2006). Extensive testing has shown that any small amount of electromagnetic interference will significantly affect the orientation of the sensors, and EMI does not necessarily affect all of the sensors equally (Swanson 1994).

An IMU is defined as a tri-axial accelerometer and gyroscope. These IMUs are able to measure linear and angular motions in 3D space without external references. Figure 2 shows an IMU from the XSens MTX system that is currently used on today's market (University of Brighton 2013). Within this system, Euler angles are used to define the angles of rotation around the x, y, and z axes that correspond to roll, pitch, and yaw.



The sensor defines a global orientation by using rotational matrices of these three angles (Hutchison, 2011).

Performing gait analysis with systems such as this allows for portable, cost effective, convenient, and efficient method of assisting patients. These wearable sensors can be attached to any part of the body including the feet, waist, arms, and leg. Data is typically collected, and sent wirelessly to a portable computer, or to a data logging device (Tong, Granat 1999).

Although this technology has enormous potential, there are still some issues that need to be optimized such as the reliability of algorithms used to minimize or eliminate drift, and the stability of the sensor signals (Tao et al. 2012, Mayagoitia, Nene & Veltink 2002, Favre et al. 2009, Gouwanda, Senanayake 2008, Yang et al. 2012, Arai et al. 2011, Arai et al. 2008). Typically, drift is addressed by using an initialization technique and various fusion algorithms. However, when integrating angular velocity with respect to the reference frame, an offset of one axis, will give rise to large errors in another axis (Gouwanda, Senanayake 2008). Numerous studies have been done to reduce variability

of IMU outputs, and prove their effectiveness independently (Bamberg et al. 2008, Bergmann, Mayagoitia & Smith 2009, Georgoulis et al. 2003). However, IMUs are currently an underutilized technology due to the lack of evidence of their accuracy. It is apparent that the issues of repeatability and validity in comparison to the current gold standard optical motion analysis system need to be addressed, and these two systems need to be used simultaneously to further evaluate the IMUs reliability and accuracy (Yang et al. 2012, Cloete, Scheffer 2008).

Joint Angular Velocity

The gyroscope component of the IMU system measures the angular rate, or angular velocity. Joint angular velocity in the sagittal plane is defined as the rate of flexion and extension of a joint, and can therefore be affected by muscle activation and force generation (Granata, Abel & Damiano 2000). The angular velocity of a joint is the relative angular velocity (rate of rotation) of the proximal body segment subtracted from the relative angular velocity of the distal body segment. In terms of the knee, the equation below is used.

$$\omega_{knee} = \omega_{tibia} - \omega_{femur}$$

Joint angular velocity has components in three directions: flexion/extension, abduction/adduction (varus/valgus), and internal/external. It is simply a measurement of how fast the joint is moving in its respective plane (Soutas-Little 1998).

Angular velocity can be used to calculate joint power, which is defined as the product of the moment and the angular velocity (Soutas-Little 1998). Muscle power has a

high correlation to overall muscle function, and can affect overall functional activities such as walking, standing and sitting from a chair, and walking up stairs (Arai et al. 2008). Joint angular velocities, especially for hips, knees and ankles, can provide valuable insight to the diagnosis and progression of mobility-related disease, and can be used in the geriatric community as a signal of muscle functionality.

Clinical Applications

To date, gait analysis has proved to hold its greatest value in the clinic regarding patients with central nervous system (CNS) disorders, in particular children with cerebral palsy who exhibit spastic gait (van den Noort, Josien C et al. 2012). Spastic gait is known as the occurrence of a heightened stretch response of the muscles, meaning that they don't want to stretch, and the legs move in a stiff manner (Damiano et al. 2006). Children who exhibit spasticity have lower angular velocity measurements around their ankles, knees, and hips due to a lowered stretch response threshold. Spastic and stiff knee gait both affect foot clearance during swing phase by limiting maximum knee flexion achieved (Damiano et al. 2006). For patients with gait disorders originating neurologically, gait analysis laboratories often serve to prescribe treatment and assess disease after surgical intervention, as well as observing long term degenerative disorders (Simon 2004).

Parkinson's Disease

Parkinson's disease (PD) can be a debilitating disease that affects gait pattern and balance, and both of these factors increase the risk of falling (Mera et al. 2012).

Unfortunately, there are no objective tests to confirm early stage PD; these diagnoses rely on the judgment of skilled clinicians observing movements and gait patterns. This diagnostic method is highly subjective, and leaves the patient's wellbeing up to experience, rather than quantifiable data (Tien et al. 2010).

As the disease progresses, deep brain stimulation can be used to relieve typical symptoms such as resting tremor, rigidity, and Bradykinesia, which is defined as the slowness of movement (Mera et al. 2012). Gait and balance disturbances are also manifested during disease progression, and this is difficult to manage with deep brain stimulation, and as the disease progresses. There is currently no standardized protocol on how deep brain stimulation affects gait and balance, which are the two main complaints from patients. The Unified Parkinson's Disease Rating Scale (UPDRS) is a standard rating scale for PD, and can determine the risk between fallers and non-fallers. Although these methods are reliable, there is bias that is introduced by the clinicians. Quantitative kinematic data from IMUs may provide more detailed reports of gait and balance, and angular velocity would allow for better characterization of limb rotation (Mera et al. 2012).

Stroke

Stroke affects approximately 15 million people a year, and 5 million people of that population are permanently disabled (Yang et al. 2012). Regaining community-based mobility is a major rehabilitation goal for many stroke patients (Arai et al. 2011). Typically, self-selected walking speed tests are good indicators of general mobility and function after a stroke and during rehabilitation regimes (Yang et al. 2012).

Instrumented walkways like GAITRite (seen in Figure 3) are commonly used to identify temporal gait parameters, including gait speed, swing and stance of the paretic limb as well as spatial parameters such as stride length and velocity. The GAITRite system, which is a pressure-sensitive walkway, has been validated against optical motion capture systems and force plates (Greene et al. 2012). Although these systems are useful and

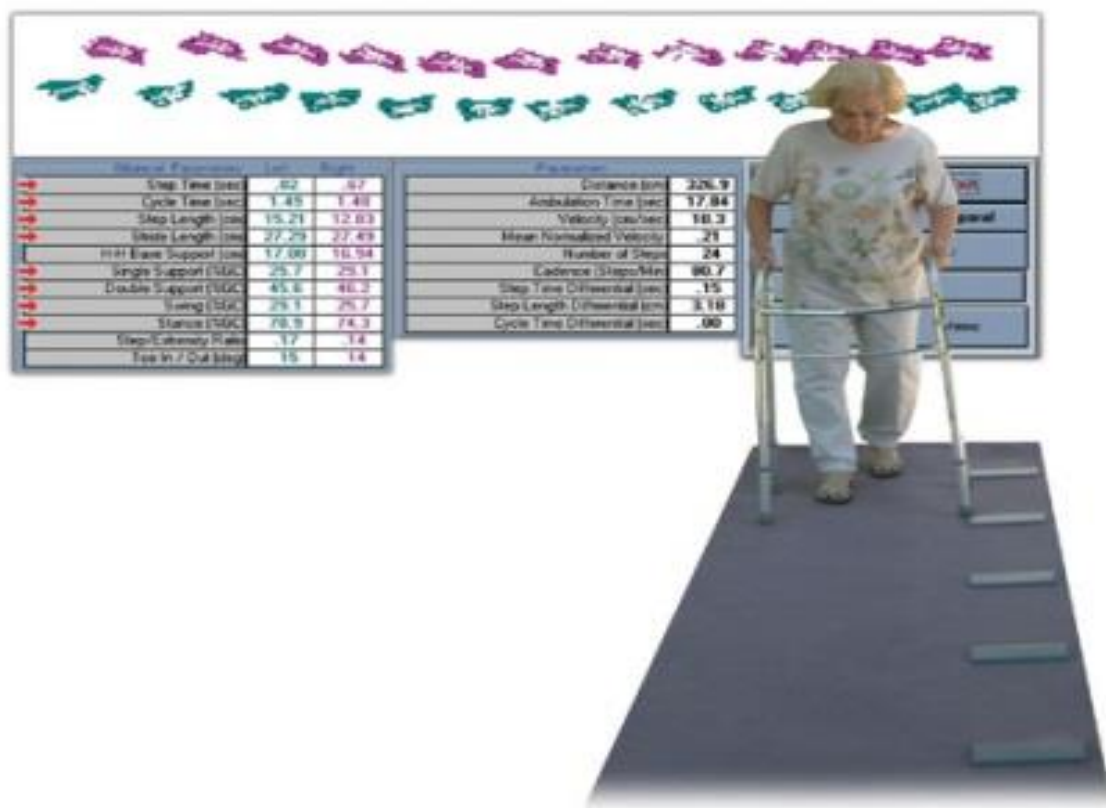


Figure 3: GAITRite mat along with data outcomes seen on a computer screen after a patient has successfully completed an analysis. (<http://www.gaitrite.com/geriatrics.html>)

comparable to other methods for obtaining spatio-temporal data, they are costly and take up a valuable space in a clinic or laboratory. IMUs can be used during post-stroke rehabilitation for the detection of gait parameters such as walking speed, and to evaluate

gait symmetry (Yang et al. 2012). Recently, two fusion algorithms have been proposed for use with gyroscopes mounted on the shank to obtain temporal gait parameters. The sensor system was validated against the GAITRite system at three walking speeds (Greene et al. 2012).

In addition to spatio-temporal outcomes, kinematic outcomes for gait are also important measures of post-stroke rehabilitation. One way that angular velocity outcomes could be utilized in the clinic is for assessing gait symmetry. Temporal parameters that are needed to evaluate gait symmetry and gait phases are typically determined from toe-off (TO) and heel-strike (HS) events. The overall temporal symmetry ratio for gait is defined as the ratio between the paretic swing-stance ratio and the non-paretic swing-stance ratio (Yang et al. 2012). Excellent correlation between shank angular velocity in the sagittal plane and at heel strike and toe off events has been found, although there have been problems in the algorithm at walking speeds less than 6.0m/s that require modification (Yang et al. 2012).

Figure 3 shows angular velocity curves that correspond to gait events important in rehabilitation (Yang et al. 2012).

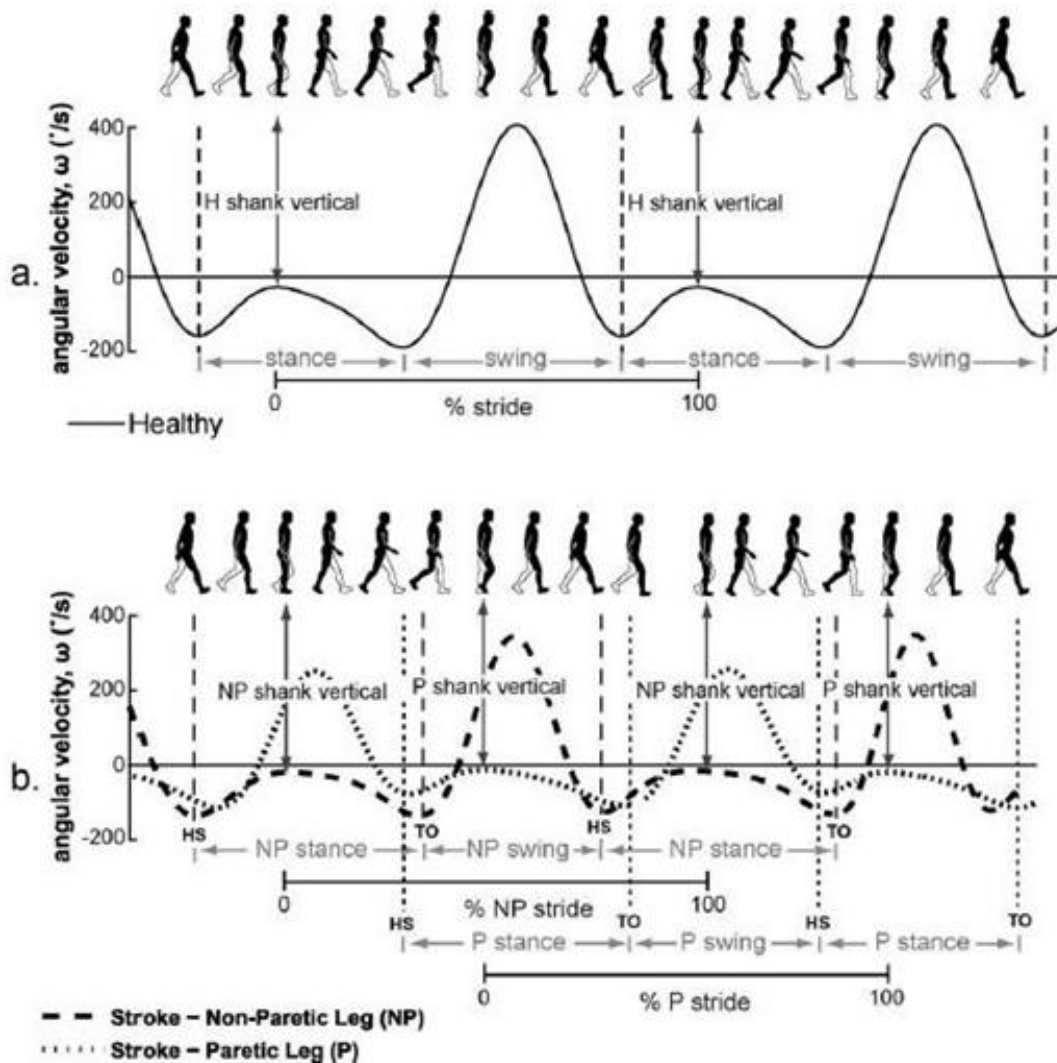


Figure 4: Gait Events that are affected by Neuromuscular Pathologies. Comparing Paretic and Non Paretic Leg (Yang et al. 2012)

Another diagnostic and rehabilitative measure for evaluating stroke victims is looking at muscle power. Muscle power can affect every day activities such as sitting and standing from a chair or walking up stairs; and decreasing muscle power can also be related to the geriatric population by risk of falling. Power is measured as the torque times the angular velocity, and therefore angular velocity can play a part in evaluating

muscle power. In particular, using angular velocity as an outcome measure after power training is commonly done in post-stroke rehabilitation regimes (Arai et al. 2011). It has been concluded that ankle angular velocities relate directly to muscle function that affects mobility in post-stroke patients, and also that angular velocity of the knee extensor had a strong relationship with a geriatric population's belief in their own physical state (Arai et al. 2011, Arai et al. 2008). When dealing with the geriatric population, it is not only important to improve their clinical outcomes, but to also improve their general sense of well-being.

Spinal Cord Injury

Spinal cord injury patients often experience spastic gait, similar to cerebral palsy patients. Typically, only injury level has been evaluated for treatment and rehabilitation measures, but spastic gait, which affects angular velocity, also needs to be an indicator of treatment for spinal cord injury patients (Krawetz, Nance 1996). Krawetz claims that kinematic data, including angular velocity, of the knees and ankles varies depending on whether the patient suffered a thoracic or lumbar injury, and this type of quantitative data can help establish rehabilitation plans as well as track progress.

Similar to stroke victims, heel strike and toe off are used to assess rehabilitation outcomes and gait symmetry in spinal cord injury victims. In addition to pressure mats such as the GAITRite, footswitches and force plates are used to identify gait events. Both of these technologies have shortcomings. Footswitches are prone to breaking, and force plates limit the overall area in which the data can be collected (Jasiewicz et al. 2006). Jasiewicz et al. conducted a study to validate that foot linear accelerations, as well

as foot and shank sagittal plane angular velocities, could correctly identify the events of foot initial contact (IC or toe-off) and foot end contact (EC or heel strike). The study showed that both foot linear accelerations and shank sagittal plane angular velocity were able to appropriately identify IC and EC in both control patients and American Spinal Injury Association (ASIA) D grade spinal cord injury patients (Jasiewicz et al. 2006).

Cerebral Palsy

Cerebral palsy, which is a central nervous system disorder, causes gait abnormalities, such as spastic gait, and most commonly affects children. To date, gait analysis has proven most valuable in clinical settings for this disorder and gait abnormality (Simon 2004). Multiple studies have shown the relation of joint angular velocity to cerebral palsy, and the overall reduction of this kinematic parameter as compared to normal patients.

Clinical evaluation looks particularly at joint movements in the sagittal plane, corresponding to flexion and extension motion. Granata et al. showed that for analysis of patients with CP exhibiting spastic gait, joint angular velocity data was a better determinant than joint angle data for comparing gait patterns between a control and CP population (Granata, Abel & Damiano 2000). Piazza et al. correlated knee angular velocity to knee muscle activity for further understanding of the swing phase of gait since a lack of flexion and extension can cause falls or trips (Piazza, Delp 1996). Damiano et al. concluded that children with cerebral palsy had slower peak knee angular velocities and less total forward movement for a complete gait cycle than normal children (Damiano et al. 2006).

Studies by Piazza et al. and Granta et al. used a VICON motion capture system, and Damiano et al. used isokinetic equipment to obtain angular velocity data. It is apparent that there is a strong correlation between angular velocity and spastic gait hallmark events seen in CP, as well as other neuromuscular disorders. Using an ambulatory system for evaluating people with CP would not only significantly reduce cost, but also allow for patients' movement to be analyzed in a variety of setting outside the gait laboratory, such as in their own homes.

Summary of the Literature

With the emergence of ambulatory, lightweight and cost effective motion analysis technology such as IMUs, there is a plethora of opportunities to adopt these technologies into a clinical environment. While cerebral palsy treatments and interventions are established, there is always room for improvement in the data collection process to minimize time and cost. It is also apparent that there is fundamental need for diagnostic and quantitative measurement techniques for other central nervous system disorders.

Despite advantages over optical motion capture systems, motion analysis results with IMUs have yet to be adopted by clinicians. Many studies have shown great promise for the use of IMUs with rehabilitation and diagnostics. By working to improve algorithms, reduce drift, and establish validity and reliability of IMU systems in direct comparison to commonly used camera systems, these technologies can be incorporated into rehabilitation and physical assessment regimes allowing for quantitative data to establish appropriate treatment.

Research Objectives

The purpose of this study is to evaluate angular velocity measurements during normal human motion as measured simultaneously by IMU and camera-based systems. In particular, this study evaluated the precision and accuracy of both individual systems. It is hypothesized that the IMU system will have higher precision for angular velocity considering angular velocity is directly measured by gyroscopes, whereas the camera system has to process position data to obtain angular velocity, introducing errors due to data processing.

Accuracy of the IMU system with respect to the “gold standard” camera system will be evaluated as well. It is hypothesized that the camera system and inertial sensors will have more correlation at lower angular velocities. In a robot arm validation study, the inertial sensors proved to be repeatable for measurements of angular displacement (analogous to joint angle) for limited angular rates and differences between the two systems was seen at the beginning of swing phase (Hutchison 2011). In a patient study done by Hutchison, highest agreement between an IMU and camera based system measurements for knee angles occurred during flexion/extension knee joint motions, with less agreement for varus/valgus and internal/external rotations. Lag in angle measurements were seen at higher angular rates, particularly at the beginning of swing phase (Hutchison 2011).

CHAPTER II – COMPARISON OF ACCURACY AND PRECISION BETWEEN CAMERA AND IMU SYSTEMS

Materials and Methods

Data Collection

Four normal subjects (1 female and 3 males) were included in this study, and ten walking trials were conducted for each. Data was collected simultaneously with the Qualisys Pro-Reflex 240 Hz eight camera system (Qualisys Motion Capture Systems, Gothenburg, Sweden) and the XSens MTx system (XSens Technologies, Enschede, The Netherlands) for all subjects. Data was collected using Labview software with a customized Labview program (National Instruments, Austin, TX). The XSens sensors use an algorithm based on an Extended Kalman Filter (EKF) that predicts future values of angular displacements based on the previous readings (Hutchison, 2011). The EKF helps guard against the effects of body motion and temporary magnetic disturbances (Sabatini 2006).



Figure 5: Initialization positions to minimize drift associated with yaw (IE) and align object axes. Projected horizontal component (left) and vertical position (right). (Adapted from Hutchison, 2011)

Sensors were placed on thigh, shank, and foot segments. Thigh and shank sensors

allowed for knee motion to be assessed, which shank and foot sensors allowed for ankle motion to be assessed. The sensors on the shank were placed superficial to the IT band; the sensors on the shin were placed superficially to the mid-shaft of the tibia; and the sensors on the feet were placed superficial to 2nd and 3rd tarsometatarsal joints (Hutchison, 2011).

For this study, due to the magnetometer being disabled to minimize EMI interference, an initialization technique was used to orient the x and y axes. This technique was used to minimize drift within the measurements throughout the data collection process. Figure 5.0 shows an example of the initialization technique, which was established by Hutchison (2011). The initialization technique is a two-step procedure adopted by Favre et al. (2008). One leg is first initialized with all body parts vertical and facing forward to allow for a +x axis alignment. During this step, accelerometer and rotation matrices were stored for each sensor. Next, the specific leg was abducted so that the thigh and shank sensors were oriented with the +y axes, allowing for a component pointing upwards. During this step, accelerometer data for each sensor was stored. This initialization technique allows for sensor-to-object and object-to-ground reference rotational matrices to be established for data collection (Hutchison, 2011).

Data Analysis

Angular and angular velocity data of knee movements were collected, processed, and normalized. All data analysis was completed using Excel spread sheets and arithmetic functions. The movements selected for analysis in this study were knee flexion/extension (FE), varus/valgus (VV), and internal/external (IE) rotations. Angular

velocities Gx, Gy, and Gz were obtained along the axes in the 3-D coordinate system corresponding to the three angular motions, respectively. Sensor data to be normalized were extracted from shank data which was taken relative to the thigh coordinate system. The third gait cycle within each walking trial was selected for analysis to represent walking with no acceleration, excluding data for incomplete gait cycles, and the flexion/extension graph was used to find instances of heel strike. Once one full gait cycle was obtained, data was normalized to 101 points, representing 0 to 100 percent of a gait cycle. Camera data was obtained similarly, by identifying the third gait cycle and normalizing the data to 101 points. For each subject and limb, all trials were averaged to find average knee angles and angular velocities.

Data Comparison

Coefficients of variations (COV), linear correlation graphs, and linear regression analyses were used to evaluate the procession and well as accuracy for the two systems.

The COV, or also known as the relative standard deviation, was used to evaluate variability within each system. This measurement shows the variability in relation to the mean population. COV's closer to zero are ideal, which is indicative of a low standard deviation, and thus less variability within the data.

$$COV = \frac{\sigma}{|\mu|}$$

The COV's were calculated by taking the standard deviation of all trials of a subject's right or left leg, and dividing that value by the average. The COV for each data point was calculated and the absolute value was taken. The COV's were then averaged over all 101

data points to obtain an average COV for one subject's limb. Each trial for each subject's limb was evaluated in the same manner. Data points with a 0 average were excluded. A two-tailed, paired *t*-test was performed in Excel to evaluate if the COVs between the two systems were statistically different.

Linear correlation graphs were plotted to evaluate the accuracy of the IMU system in comparison to the camera system, with the assumption that the camera system data set is correct. Ideally the plot would be a straight line with a slope of 1 and would intersect at zero, indicating perfect alignment of the data points between both systems. Average angular velocities for each limb of each subject were plotted with camera data on the x-axis, and IMU data on the y-axis. Areas of linearity were visually indicated, and further statistical tests were performed to assess what percentages of the gait cycle exhibited co-linear portions (i.e. data agreement).

F-test analyses were run on linear regression models in Statistical Analysis Software (SAS) to statistically determine areas of co-linearity within the 101 points of the gait cycle, and at different intervals of angular velocities. All subject data were analyzed as a single data set, treating each trial as independent. The first linear regression analysis included the averages of the camera and sensor data for all subjects. A Bonferroni correction of 100 was used for this analysis, as there were approximately 100 data points per trial. This adjustment involved dividing the P value at which significance was detected (0.05) by 100, to avoid the chance of type 1 errors, or incorrectly rejecting the null hypothesis that the data from the two systems are statistically equivalent (Napierala, 2012.). The new P value for this analysis for rejecting the null hypothesis was $P >$

0.0005. The second linear regression analysis looked for co-linearity of angular velocity measurements between the camera and IMU systems at $5^{\circ}/s$ intervals, ranging from $-200^{\circ}/s$ to $200^{\circ}/s$ with a P value of 0.05.

Results

Coefficient of Variation

Table 1 shows the average COV values between all four subjects in the study.

Table 1: Coefficients of Variation (COV) for angular velocities of the knee averaged over multiple trials for each subject and limb. Average COV values for sensor and camera systems in each plane of motion shown in bottom row.

Subject	Gx_S	Gx_C	Gy_S	Gy_C	Gz_S	Gz_C
1 Left	0.3538	2.2861	7.3434	3.6019	3.8340	2.9194
1 Right	0.9708	1.0470	1.2225	2.0552	5.7477	8.7607
2 Left	0.5851	0.4163	3.6110	1.8144	1.9900	7.7443
2 Right	1.1112	0.4678	4.4662	7.2550	2.6733	2.9244
3 Left	0.8443	0.4595	3.2037	3.2861	2.1271	9.1901
3 Right	0.1799	0.0683	0.7645	2.2640	5.1287	1.3502
4 Left	0.0966	0.5587	2.1839	3.8526	1.9860	2.0378
4 Right	2.1493	8.3028	1.6896	12.1414	1.6825	1.5462
Average COV Values	0.7864	1.7008	3.0606	4.5338	3.1462	4.5591

COV values for knee angular velocity measurements around the axes of flexion/extension rotation (Gx), internal/external rotation (Gy), and varus/valgus rotation (Gz) were compared for the camera (C) system and the IMU sensor (S) system for each subject and trial. Although COV values for the sensor system were lower than those for the camera system, *t*-test results showed that they were not significantly different at a significance level of 0.05.

The average of all trials, as well as standard deviations for Subject 3 and are shown in Figures 6 a-c. This subject was chosen to show areas of agreement within the two systems.

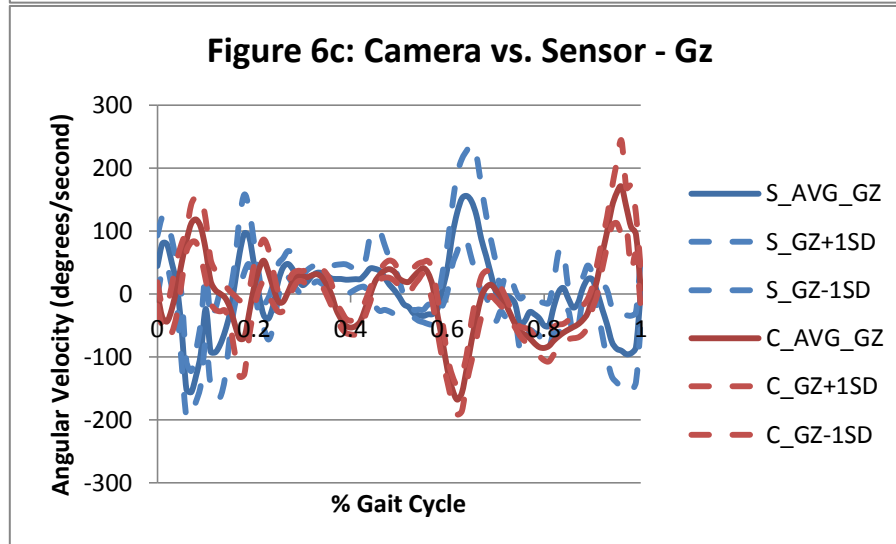
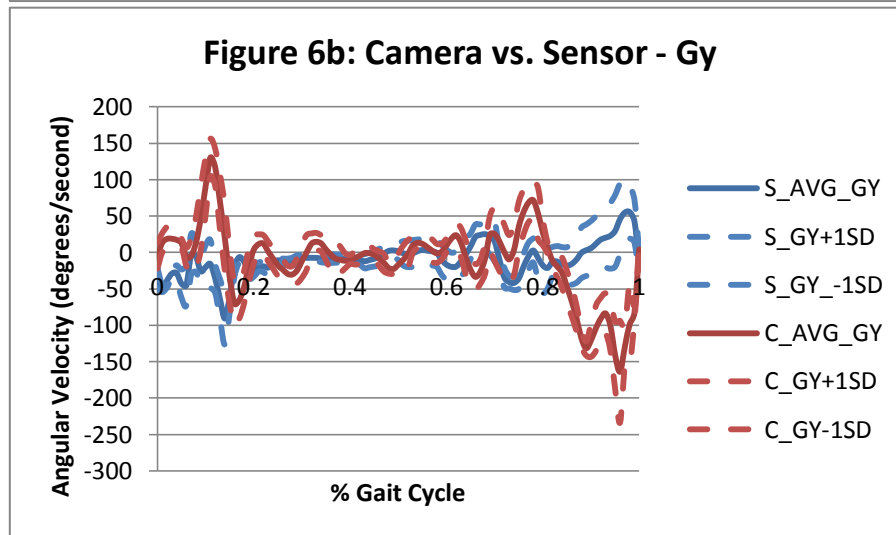
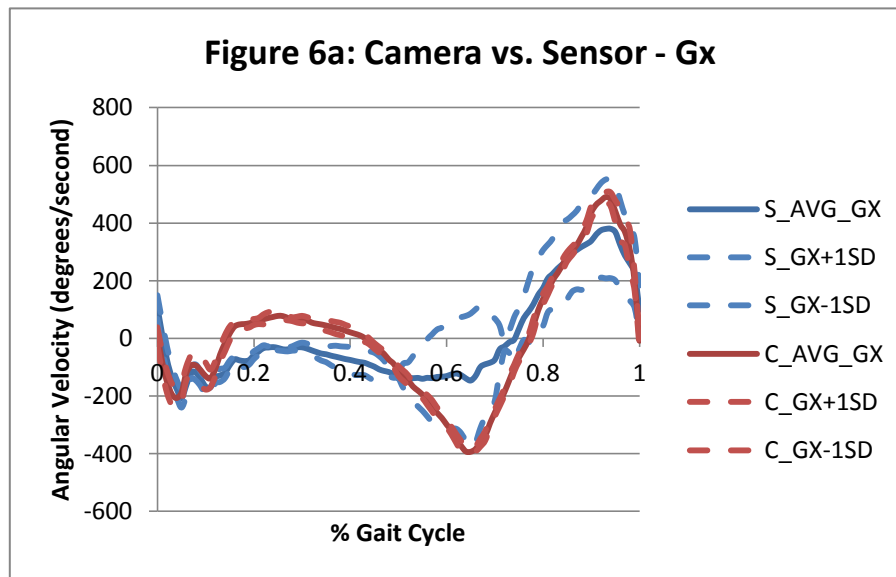


Figure 6: Comparison of camera system and IMU system of knee angular velocity of Subject 3 for 1 gait cycle. Gx (top), Gy (middle), Gz (bottom)

Average sensor angular velocities were plotted against average camera angular velocities for each subject and trial to evaluate areas of linear correlation for each rotational axis. Subject 3 linear correlation graphs are shown in Figures 7 a-c.

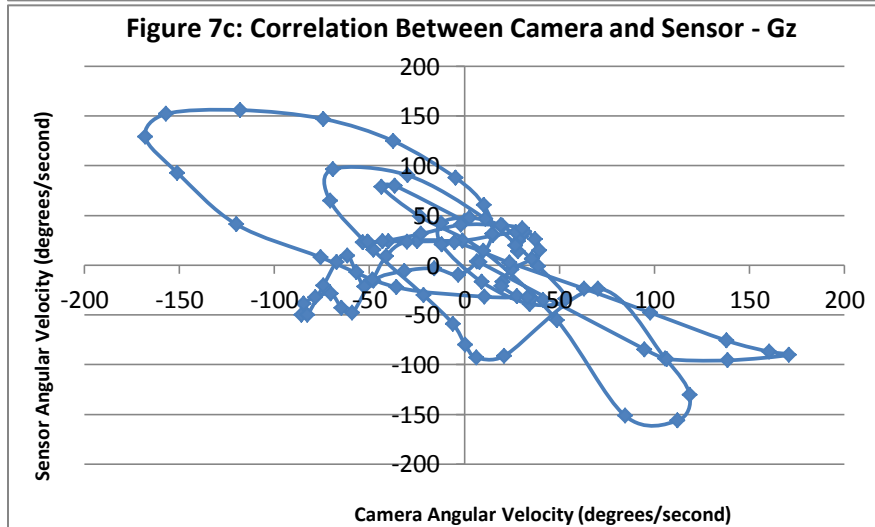
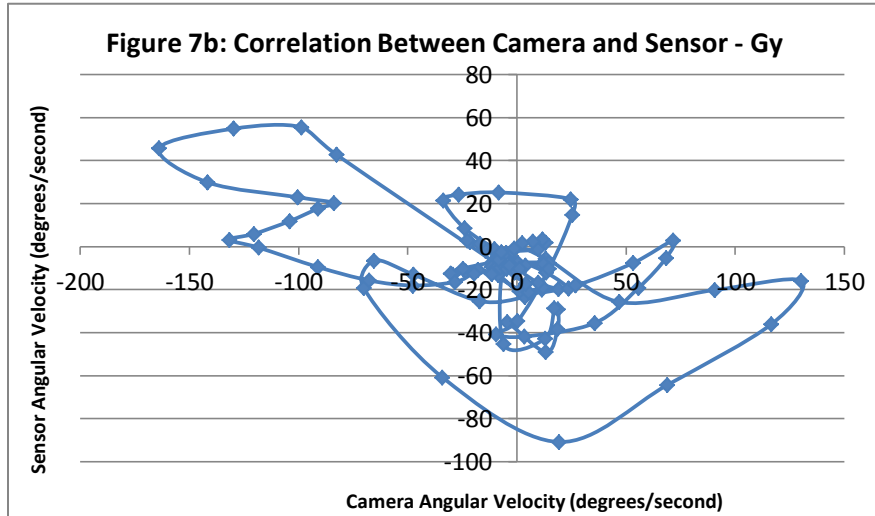
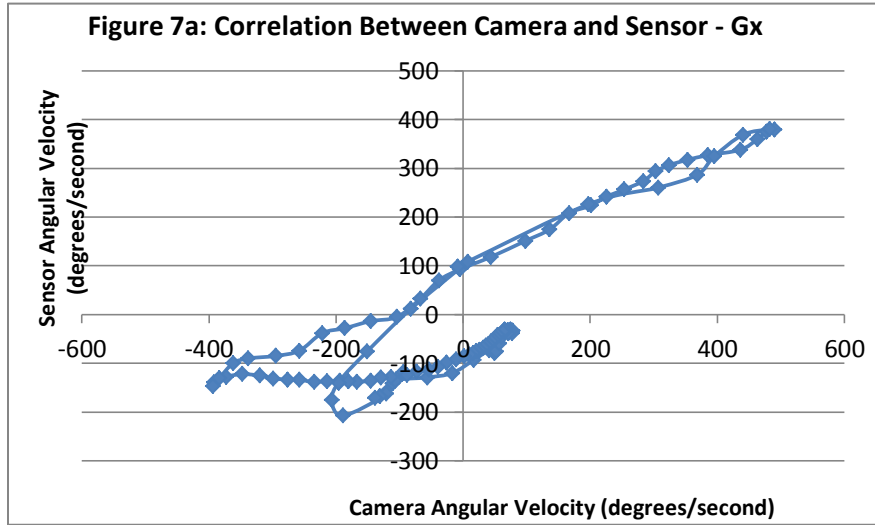


Figure 7: Evaluation of linear correlation between camera and sensor systems for Subject 3 for 1 gait cycle. Gx (top), Gy (middle), Gz (bottom). Data points represent points within gait cycle and are shown to evaluate clustered area.

Linear Regression Analyses

Table 2: Percentages of Gait Cycle In which co-linearity occurred

Gx	Gy	Gz
0.08-0.12	0.06	0.06-0.17
	0.08-0.11	0.19-0.20
	0.14-0.17	0.24-0.25
	0.24	0.31-0.39
	0.32-0.40	0.41
	0.65	0.52-0.61
	0.86	0.67-0.74
		0.99-1.00

Table 2 shows the portions of the gait cycle that are significantly not different for the linear correlation between the camera and IMU system. Figure 8 is a visual representation of the areas within the gait cycle in which the two systems are co-linear. The plot is a typical flexion-extension knee joint angle curve.

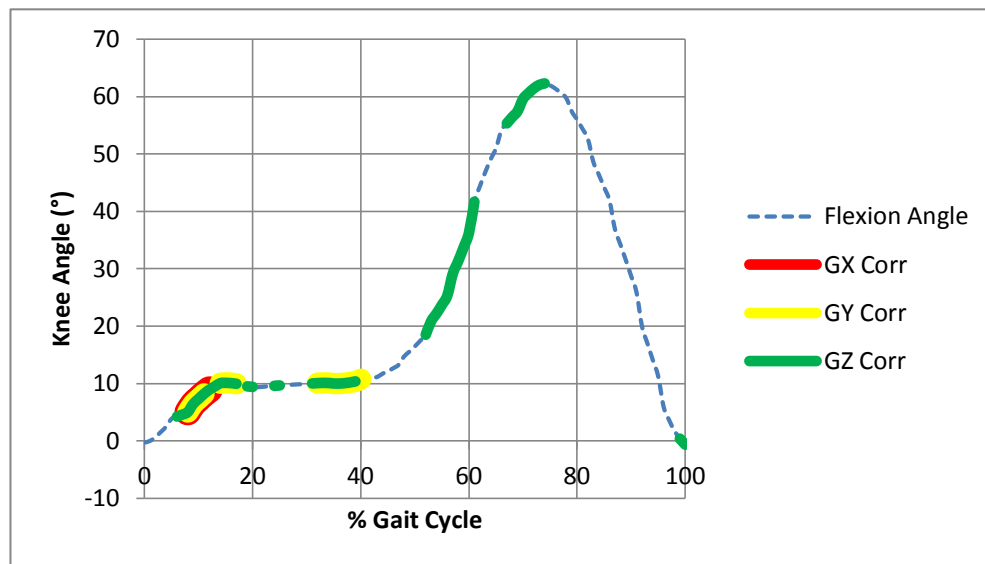


Figure 8: A Visual Representation of co-linearity between camera and sensor systems plotted against a typical knee flexion-extension angle curve

Table 3 and Figure 9 show the ranges of angular velocities in which angular velocity measurements of the camera and IMU system linearly correlated.

Table 3: Ranges and points of angular velocities at which camera and sensor angular velocities are co-linear

Gx	Gy	Gz
-200 -195	-190	-200 -195
-175 -170	-175	-185 -175
-160 -110	-145	-145
-100 -30	-135	-95 -85
100 110	-40	-55
130 175	0	-45
180 200	85 90	-25
	105	5
	130 185	20
	145	35
	155	50
	165 170	75 80
	185	110 115
	200	130
		140 150
		160 165
		180
		190 200

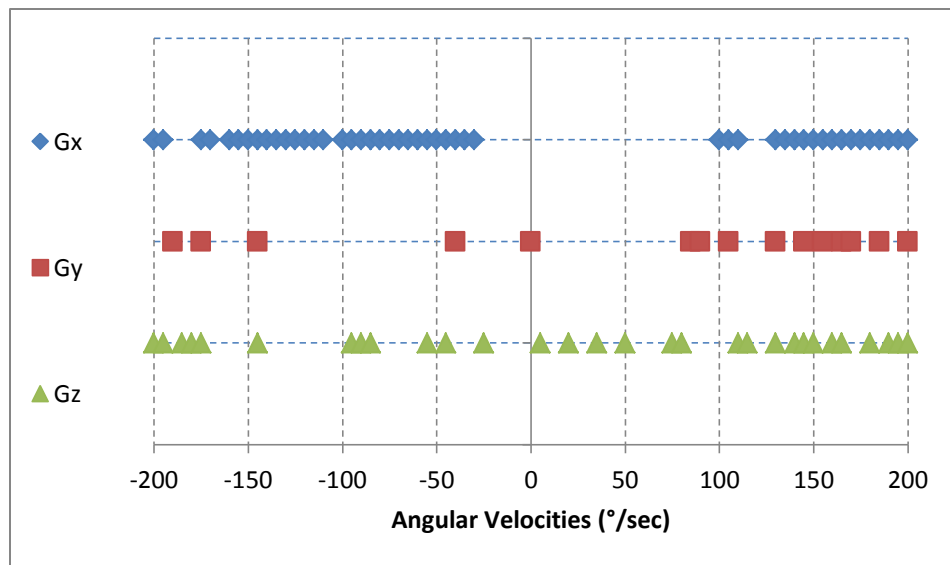


Figure 9: Ranges and points of angular velocities at which camera and sensor angular velocities are co-linear

Discussion

Table 1 shows that the lowest overall COV values occurred for both camera and sensor angular velocities around the flexion-extension plane of motion (sagittal). Hutchison found the highest agreement with knee angles between camera and IMU systems in the sagittal plane for normal gait trials (Hutchison, 2011). It was hypothesized that the COV's for angular velocity would be lowest in the sagittal plane. The COVs for the sensor were lower than COV values for the camera for every plane of motion. This was to be expected, and can be attributed to the fact that the sensor gyroscopes directly measure angular velocity, whereas the camera system has to integrate position data twice to obtain the same output. As hypothesized, the sensor system is more repeatable, and less variable within its own system. However, no statistically significant difference was seen between the two systems for their values of COVs. Some of the significance that may have been detected within the study could have been masked due to the variability between trials for each subject. The lack of statistical significance is also likely tied to the lack of accuracy in quantitative measurements between the two systems.

Linear correlation graphs, seen in Figures 6 a-c show the sensor angular velocities plotted versus the camera angular velocities. An ideal plot would have a slope of 1, and intersect at zero. The only graph that has portions resembling this pattern is Figure 6a, which portrays angular velocity around the x-axis (flexion-extension). The other axes showed small areas of co-linearity, but were hard to distinguish with the naked eye. There were also clusters of data points that may or may not have been co-linear; this indicated a need for statistical analysis of the co-linearity of the data.

Table 2 shows at what percent of the gait cycle the camera and sensor data are co-linear. The null hypothesis for this data was that the slope was 1 and had an intercept of zero. The P-value was set to 0.0005 using the Bonferroni correction, and all values below this were rejected. In agreement with visually observing linear correlation graphs, the data was co-linear from 8-12% of the gait cycle for Gx. There were short, intermittent occurrences of co-linearity for Gy and Gz, but there was no trend seen among the data except for co-linearity at approximately 8-12% of the data for all three angular velocities. Figure 8 is a visual representation of areas within the gait cycle in which the two systems are co-linear over a typical flexion-extension knee joint angle graph.

Since a distinct pattern among the data was not seen with the linear regression analysis between camera and sensor evaluated against the gait cycle, co-linearity between data sets was evaluated at $5^{\circ}/s$ intervals of angular velocity values, with the assumption there would be greater co-linearity at lower angular velocities. Figure 9 and Table 3 shows the ranges of angular velocity at which the camera and sensor data were co-linear. Again, there was no distinct pattern in these results, and the areas of co-linearity were not seen at low angular velocities, as hypothesized.

CHAPTER III – CONCLUSIONS AND FUTURE CONSIDERATIONS

The results of this study show promise for the continued study of IMU systems. The data analysis for this study showed that the IMU system measurements of joint angular velocities are repeatable. There were limitations in this study that should be addressed and considered for future studies. The study population used in this study was small, only having four subject to evaluate. The data comparison was against two separate systems that do not obtain data in the same manner, nor are they comparable in set up or calibration/initialization technique; in other words, they are both models of motion, not direct measurements. Each system will have error due to the fact that the markers and sensors are not directly attached to the bone. Soft tissue artifacts are a known issue with camera based motion capture systems (Sadeghi et al. 2000), and this is likely also the case with IMU systems.

The literature has shown that IMUs hold great promise for use in clinical laboratory settings, as well as many other applications. However, drift is an issue with IMU data collection, and is addressed in the literature surrounding this technology and studies conducted using IMUs using specialized software, initialization techniques, and algorithms (Tao et al. 2012, Mayagoitia, Nene & Veltink 2002, Favre et al. 2009, Gouwanda, Senanayake 2008, Roetenberg 2006, Swanson 1994, Arai et al. 2011, Arai et al. 2008). Drift was most likely a source of error in this study, but can be alleviated with incorporating more effective algorithms and initialization techniques.

For future studies and consideration for using this technology in clinical applications, there are many studies that can be conducted. First, a power study should be

conducted in order to evaluate the appropriate sample size to be used, as well as identifying the minimum angular velocity difference between the two systems to be statistically significant. Knowing that human gait is not the same for everyone, one future study could evaluate specific motions in which motion capture systems correlate, by having subject repeat a statistically relevant number of walking trials and evaluating heel strike, toe off, and the beginning of swing phase for agreement. Another study set up to evaluate specific motions could have subjects flex and extend their knees and ankles while being stationary. Other sensors should also be evaluated for use in human motion analysis. There are other IMU sensor systems such as the Memsense Wireless (<http://memsense.com/products/wireless>), that have smaller geometric dimensions, which would leave the sensor with a lower profile against the skin, and would likely be less prone to drift and soft tissue artifacts. To address the lack of statistical significance between the two systems' COVs, a robot arm validation study should be completed with simultaneous data collection with a sensor and camera system. In this study, variability was introduced by the subjects, and the robot arm would eliminate that variability. Newer algorithms should also be incorporated into any future studies, which would likely reduce the effects of drift.

Overall, this study along with many others shows the feasibility for IMUs as a tool in clinical, laboratory, and rehabilitative environments. By improving the technologies used to assess patient outcomes and rehabilitation progress, it is hoped that overall patient well-being can be improved. Using low-cost, lightweight, and easy to use systems will not only help clinicians, but also patients. Improvements to various filters or

algorithms, as well as more refined initialization techniques to reduce the effects of soft tissue artifacts and drift may all help with the implementation of IMUs in the clinical environment as a replacement to the conventionally used camera-based systems for specific medical conditions.

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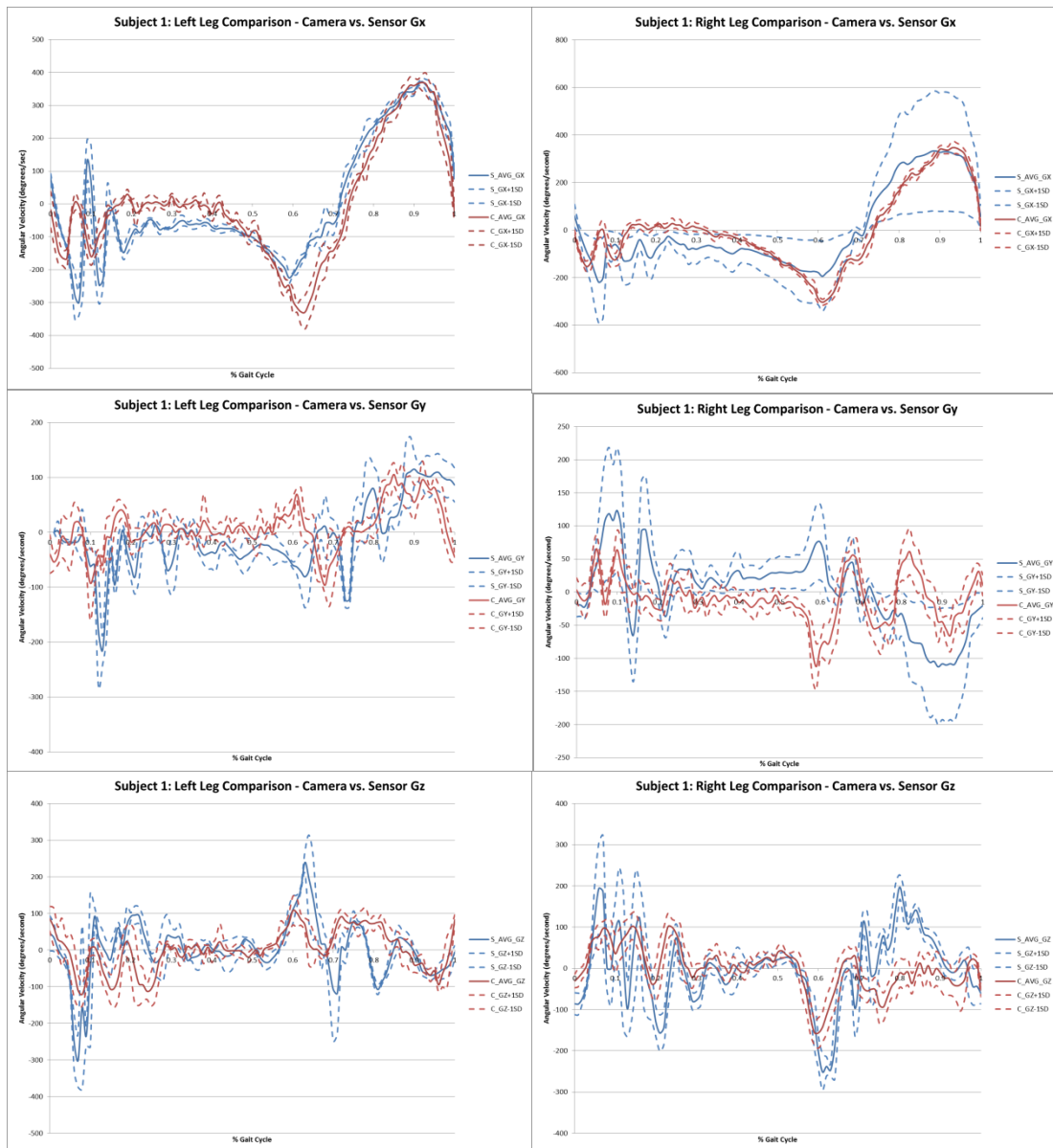
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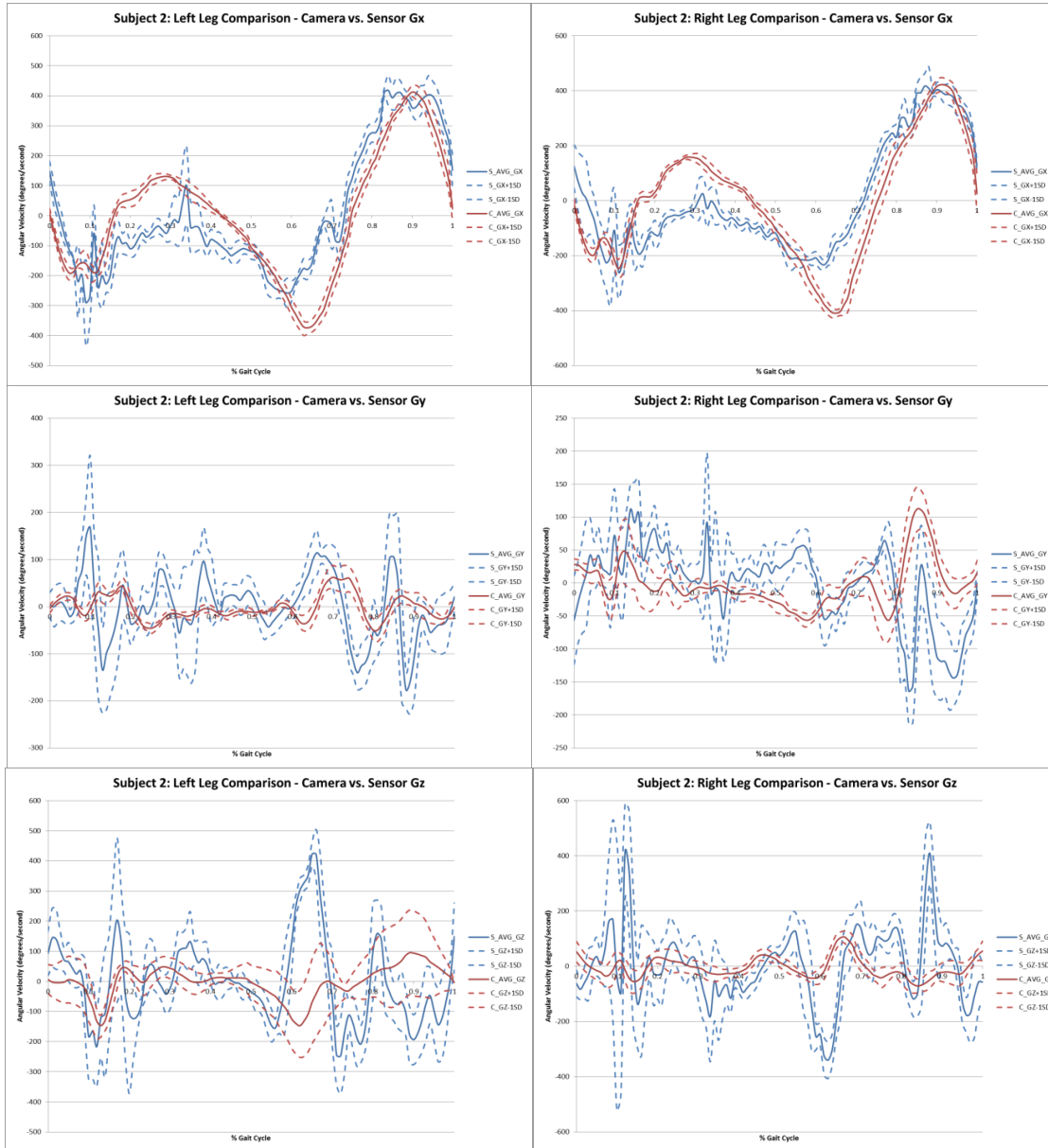
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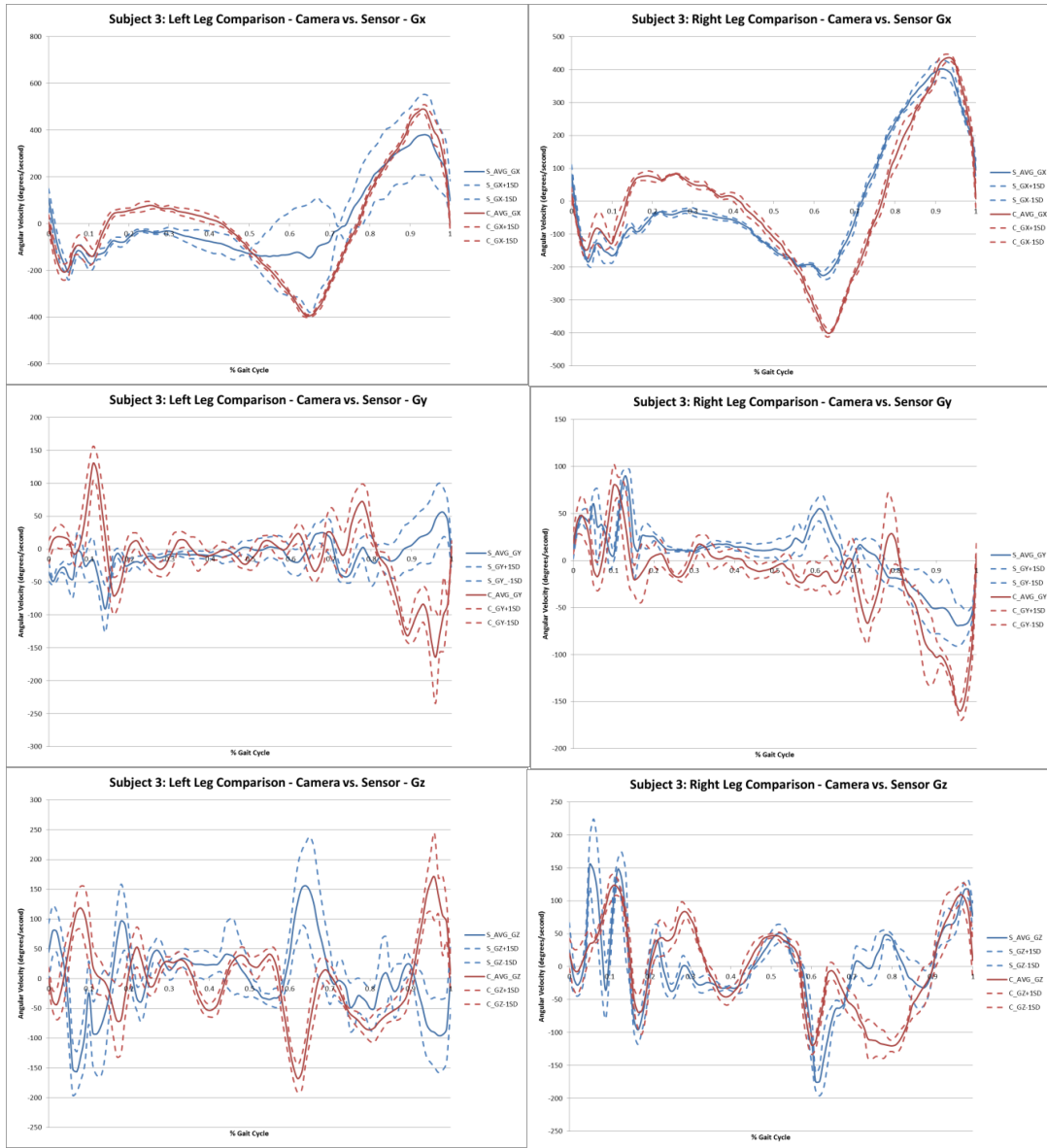
APPENDICES

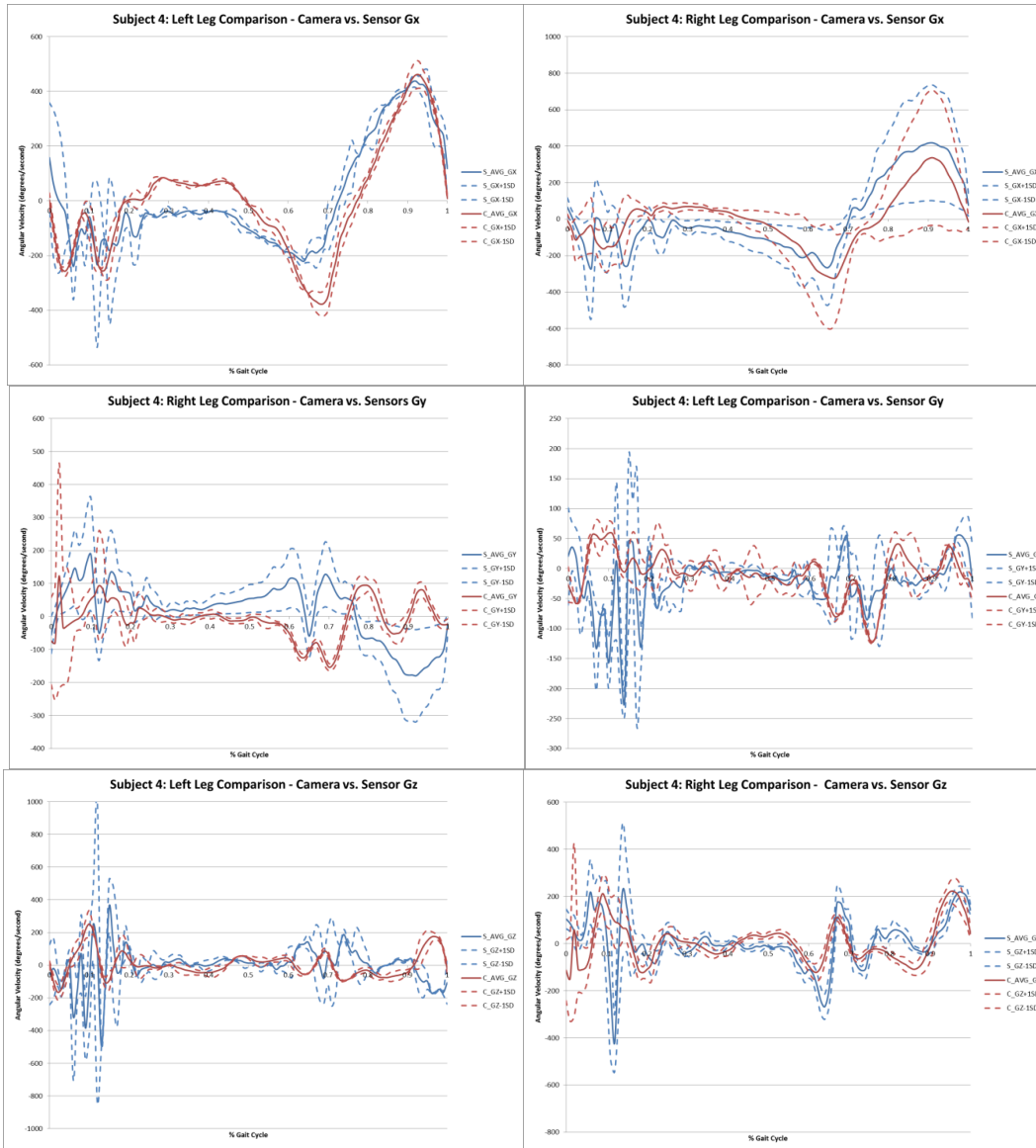
Appendix A: Camera vs. Sensor Data

Figure 10: Comparison of camera system and IMU system of knee angular velocity for walking gait of 4 subjects.









Appendix B: Linear Correlation Graphs

Figure 11: Linear correlation between camera system and IMU system of knee angular velocity for walking gait of 4 subjects.

